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Hybrid Neuro-Fuzzy System for Optimal Generation scheduling in Electrical Power systems

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Abstract : *The real time controls at the central energy management center in a power system, continuously track the load changes and endeavor to match the total power demand with total generation in such a manner that the operating cost is least. Conventional optimization techniques are cumbersome for such complex optimization tasks and are not suitable for on-line use due to increased computational burden. This paper proposes a neuro-fuzzy power dispatch method where the uncertainty involved with power demand is modeled as a fuzzy variable. Then Levenberg-Marquardt neural network (LMNN) is used to evaluate the optimal generation schedules. This model trains almost hundred times faster that the popular BP neural network. The proposed method (Hybrid Neuro Fuzzy System) has been tested on two test systems with six and thirteen generating units and found to be suitable for on-line economic dispatch.*
Keywords: *Economic dispatch (ED), Lambda iteration method, Gaussian membership functions, linguistic categories, Price penalty factor, Levenberg Marquardt algorithm, Hybrid Neuro Fuzzy System (HNFS)*

I. Introduction

The basic objective of economic load dispatch of electric power generation is to schedule the committed generating unit outputs so as to meet the load demand at minimum operating cost while satisfying all units and system equality and inequality constraints. Main aspect of economic load dispatch is the on line economic dispatch where in it is required to distribute the load among the generating units actually paralleled with the system in such manner as to minimize the total cost of supplying the minute to minute requirement of the system. This problem is solved traditionally using mathematical programming based on optimization techniques such as lambda Iteration method, gradient method and dynamic programming method [1-3].

The classical lambda-iteration method has been used by power utilities for economic load dispatch (ELD). In Lambda iteration method convergence of the iterations is affected by the initial choice of lambda. Two types of iterations are involved in this method. First, lambda moves from its initial assumed value to its final optimal value iteratively. For systems with many generators, this movement can be oscillatory and may increase the computational time. Secondly, for each trial value of lambda, the associated generations have to be obtained using sub-iterations. Thus, the sub-iterations have to be involved many times. Therefore, this method could become too time consuming for effective real-time implementation.

Various artificial neural network based methods have been proposed for the ED problem [4-10]. Application of Hopfield method [4,5] and BP based methods [6-9] converge very slowly and suffer from local minima problem. Two phase neural network [9], Radial basis function [10] and Levenberg-Marquardt algorithms [11] have also been proposed as they do not suffer from these slow convergence problems. Recently there is an upsurge of hybrid methods [12-13] based on alternate approaches such as neural network and fuzzy logic due to their ability to model vague and noisy practical problems effectively. Approaches based on quadratic programming [14], fuzzy satisfaction maximizing technique [15], and genetic and evolutionary programming based hybrid approaches [16, 17] have been proposed for this problem.

In most of the common Multi-layer perceptron neural networks (MLP), the training is based on non-linear optimization techniques. All these methods suffer from local minima problems, tend to converge very slowly and do not always achieve global minima. Several high performance algorithms are developed to train MLP models that converge 10 to 100 times faster than BP algorithm. These algorithms are based on numerical optimization techniques like conjugate gradient, quasi Newton and Levenberg-Marquardt algorithms. Out of these, Levenberg-Marquardt algorithm is found to be the fastest method for training moderate sized feed-forward neural networks [18-19].

In this paper, a hybrid model has been developed for on-line economic dispatch which uses fuzzified inputs for training Levenberg-Marquardt neural network (LMNN).. In this paper, the efficiency of the hybrid LMNN (HNFS) has been demonstrated for the ED problem on 6 and 13-generating unit systems taken from reference [20].

II. Methodology

The block diagram of the proposed hybrid neuro-fuzzy approach is shown in Fig 1. A large number of loading patterns are generated in wide range of loads as shown in block I, and for each value of total power demand, the ED problem was solved using conventional lambda iteration method [1] to obtain optimal dispatch among the generating units [1], (block II). The generated power demand is fuzzified into different linguistic categories (block III). A large number of input-output patterns are thus generated to train the LMNN, taking fuzzified total power demand as the input. The trained LMNN (block IV) estimates the optimal power dispatches as well as operating cost for unknown patterns instantaneously.

2.1 Optimal Generation Scheduling

The objective of economic load dispatch is to minimize the total generation cost in a power system for a given load while satisfying various constraints. Thus economic dispatch is a constrained optimization problem and can be formulated as

Minimize the overall cost of generation

$$C = \sum_{i=1}^{m} C_i(P_{Gi}) \tag{1}$$

Subject to the inequality constraint

$$P_{Gi}^{\min} \leq P_{Gi} \geq P_{Gi}^{\max}, \quad i = 1, 2, 3 \ldots\ldots\ldots m. \tag{2}$$

and equality constraint of meeting the load demand with the transmission losses, i.e.

$$\sum_{i=1}^{m} P_{Gi} - (P_D - P_L) = 0 \tag{3}$$

For a given real load P_D at all the buses, the system loss P_L is a function of active power generation at each generating unit. To calculate system losses, two methods are in general use. One is the method of penalty factors and the other is the use of constant loss formula coefficients or B-coefficients [1,2]. The latter is commonly used by the power utilities and is adopted in this study. In this method, transmission losses are expressed as a quadratic function of generations:

$$P_L = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_j \tag{4}$$

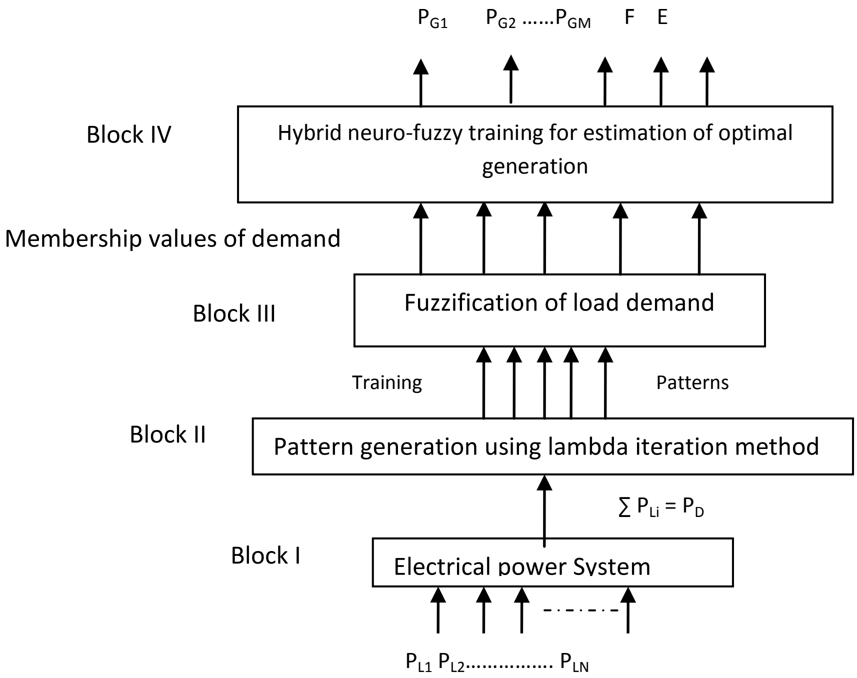
Fig.1 shows the block diagram of the economic optimal generation scheduling in a conventional power system. The main challenge for stable and reliable operation of an electric power system is to match the generation with the loads, under continuously varying system conditions including demand, supply and contingencies. The objective is to assign generations at connected generating units of the system in such a manner that the cost of operation is minimum while all the operating constraints are satisfied. This is a complex time intensive task for which optimization programs are run to compute the optimal values of real power generations every half an hour or so. When the optimal values are available, the appropriate control actions are taken through Automatic Generation Control (AGC) involving governor control and adjustment of valve setting adjusting fuel supply such that the units generate optimal allocated values.

2.2 Hybrid Approach for ELD

In the proposed hybrid approach, a large number of loading patterns were generated in wide range for the system under study. The generated patterns are fuzzified to include the uncertainty involved with power demand. Four fifth of the input-output pairs thus generated, are used to train the neural network. In order to speed up the neural network training, Levenberg-Marquardt BP algorithm is applied.

2.3 Fuzzy modeling of load demand

The power system load demand constantly changes and for each demand level optimum generation allocation is to be found. Development of probabilistic load models poses problems due to lack of proper and consistent field data. On the other hand fuzzy load data is presented in the form of possibility distributions of loads where the membership values can be derived from qualitative assessment, linguistic declarations, operator's past experiences or heuristics. In contrast to the conventional deterministic/ probabilistic load models, the proposed approach includes the stochastic behavior of loads by modeling them as fuzzy quantities having membership values in different linguistic categories. The incorporation of fuzziness in on-line applications is effective as the data available at the energy management center is normally vague, noisy and irrelevant.



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To model the uncertainty associated with load demand it is fuzzified into different linguistic categories. For the fuzzy representation of power demand, membership values in the range of 0 to 1 are assigned to each pattern generated. Thus crisp demand values are converted to fuzzy values. Load uncertainty is modeled by representing it as a fuzzy variable with memberships in different fuzzy linguistic categories, such as, very small (VS), small (S), medium (M), large (L) and very large (VL). The boundaries of these categories are fuzzified based on intuition and experience. Every load value in the crisp set is assigned membership values that represent the possibility of load being in that category. Non-linear guassian membership functions are used to find the membership values of P_D in different fuzzy categories. In place of the more common triangular or trapezoidal functions, non-linear membership functions are found to be more suitable for representing power demand, as they ensure a smoother and more practical transition of loads from one category to the other. Also it does not add any complexity to the model. The membership value (μ) is calculated as [20]

$$\mu_i = \frac{1}{1+\left[\dfrac{P_D - a_i}{b_i}\right]^4} \tag{5}$$

a_i and b_i are parameters corresponding to linguistic category *i* of power demand. These values can be chosen keeping in mind that a_i represents the central value of the corresponding category, around which the membership value is equal to 1.0 and $b_{i,}$ controls the width of the corresponding category. Heuristic and past experience play a key role in deciding the parameters a_i and $b_{i,}$,. Similarly the number of linguistic categories used for modeling may also vary from system to system. Thus by changing the parameters a_i and b_i, different power systems can be modeled for any range of load variation. Table 2 and Table 7 show the fuzzification data used in this paper.

2.4 Levenberg-Marquardt Neural Network

In order to speed up the neural network training, Levenberg-Marquardt BP algorithm is applied. Various architectures of the LMNN models having different number of hidden nodes were trained for the same error goal and the optimal structure has been selected on the basis of the least training time. The trained LMNN has been found to be very fast and suitable for on-line generation dispatch as compared to the conventional methods which are slow and sometimes fail to converge.

The Levenberg-Marquardt algorithm is a variation of Newton's method [18]. This algorithm is very well suited to neural network training, where the performance index is the mean squared error and the variables *x* are weights of the network. During supervised training a set of input patterns are presented to the network along with desired outputs (obtained using conventional method). The training is started with small random weights and the network is made to adjust the weights *x* such that the difference between the network output and the target output is minimized. The mean squared error summed over *m* number of output nodes, for PT number of patterns is defined as

$$ER = \frac{1}{2PT}\sum_{PT}\sum_{m}(T\arg et_m - Output_m)^2 \tag{6}$$

Newton's update for optimizing mean squared error *ER(w)* is

$$w_{k+1} = w_k - A_k^{-1} g_k \tag{7}$$

where $A_k \equiv \nabla^2 ER(w)\big|_{w=w_k}$ *and* $g_k = \nabla ER(w)\big|_{w=w_k}$

As *ER(w)* is a sum of square function it can be written as

$$ER(w) = \sum_{PT}(T\arg er - Output)^T(w)(T\arg et - Output)(w) \tag{8}$$

then the j^{th} element of the gradient would be

$$[\nabla ER(w)]_j = \frac{\partial ER(w)}{\partial w_j} = 2\sum_{i=PT}(T\arg et - Output)_i(w)\frac{\partial (T\arg et - Output)_i(w)}{\partial w_j} \tag{9}$$

The gradient can therefore be written in matrix form

$$\nabla F(x) = 2J^T(w)v(x) \tag{10}$$

where J is the Jacobean matrix giving sensitivity. Next, the Hessian matrix is to be determined. The k, j element of the Hessian matrix would be $[\nabla^2 ER(w)]_{kj} = \frac{\partial^2 ER(w)}{\partial w_k \partial w_j}$ (11)

The Hessian matrix can then be expressed in matrix form.

$$\nabla^2 ER(w) = 2J^T(w)J(w) + 2S(w) \tag{12}$$

where $S(w) = \sum_{i=1}^{N}(T\arg et - Output)_i(w)\nabla^2(T\arg et - Output)_i(w)$ (13)

If *S(w)* is assumed to be small, the Hessian matrix can be approximated as

$$\nabla^2 F(w) \cong 2J^T(w)J(w) \tag{14}$$

Substituting (10) and (14) into (7), the Gauss-Newton method is obtained as

$$w_{k+1} = w_k - \left[2J^T(w_k)J(w_k)\right]^{-1} 2J^T(w_k)v(w_k) \tag{15}$$

From this, it is evident that the advantage of Gauss-Newton method over the standard Newton's method is that it does not require calculation of second -order derivatives. One problem with the Gauss-Newton method is that the matrix H = J^TJ may not be invertible. This can be overcome by using the following modification to the approximate Hessian matrix.

$$G = H + \mu I \tag{16}$$

To make this matrix invertible, suppose that the eigen values and eigen vectors of H are $\{\lambda_1, \lambda_2 \ldots\ldots, \lambda_n\}$ and $\{z_1, z_2, \ldots\ldots, z_n\}$

Then $Gz_i = [H + \mu I]z_i = Hz_i + \mu z_i = \lambda_i z_i + \mu z_i$ (17)

Therefore the eigenvectors of G are the same as the eigenvectors of H and the eigen values of G ar**e (** $(\lambda_i + \mu)$ **.** G can be made positive definite by increasing μ until $(\lambda_i + \mu) > 0$ **f**or all i, and therefore the matrix will be invertible. This leads to the Levenberg-Marquardt algorithm [18].

$$\Delta w_k = -\left[J^T(w_k)J(w_k) + \mu_k I\right]^{-1} J^T(w_k)v(w_k) \tag{18}$$

This algorithm has a useful feature that as μ_k is increased it approaches the steepest descent algorithm with small learning rate

$$w_{k+1} \cong w_k - \frac{1}{\mu_k} J^T(w_k)v(w_k) \tag{19}$$

and if μ_k is decreased to zero the algorithm becomes Gauss-Newton. The algorithm begins with μ_k set to some small value .

III. Results and Discussion

The effectiveness of the proposed hybrid approach for economic dispatch problem has been demonstrated on two test systems. It has been found that the LMNN trains very fast (in a few iterations) due to the effective Levenberg-Marquardt algorithm. In comparison to slow converging conventional methods this method is highly suitable for determining on-line dispatch strategy accurately in modern market driven power systems. Using this algorithm, it is easy to decide the optimum neural network architecture for a given error goal.

3.1 Six Generating Unit System

The cost coefficient and generation limits of six-unit system are given in Table 1. Transmission losses are calculated using B matrix [1] in Table 3. To establish the effectiveness of developed LMNN for ED, the neural network models are trained for 6-generating unit system. The load patterns are generated by varying the load at each bus of the system randomly. The conventional lambda iteration method was applied for each load pattern to obtain the optimum value of real power at different generating units, for minimum cost .Total 300 patterns were generated by changing load (P_D) between 900MW to 1350 MW. The generated patterns were fuzzified using eq. (6) and data in Table 3. The values in Table 4 are selected based on operator experience or expert judgment. The fuzzification of loads is represented in Fig. 2. Then 240 fuzzified patterns were used for trainings LMNN while remaining 60 patterns were used for testing the performance of the trained network. The LMNN is also capable of producing the minimum cost content corresponding to the optimal solution.

Table 1.Cost Coefficients and Generation limits of Six-unit system

S. No.	P_{imin}	P_{imax}	a_i	b_i	c_i
1	100	500	0.007	7	200
2	50	200	0.0095	10	200
3	80	300	0.009	8.5	220
4	50	150	0.009	11	200
5	50	200	0.008	10.5	220
6	50	120	0.0075	12	190

Table 2.Data for Fuzzy Modeling of Power Demand for 6-unit System

Linguistic Category for P_D	Very Small	Small	Medium	Large	Very Large
a_i	900	1000	1100	1200	1300
b_i	50	60	70	60	65

Table 3.B-coefficients of Six-unit system

0.0017	0.0012	0.007	-0.0001	-0.0005	-0.0002
0.0012	0.0014	0.0009	0.0001	-0.0006	-0.0001
0.0007	0.0009	0.0031	0	-0.001	-0.0006
-0.0001	0.0001	0	0.0024	-0.0006	-0.0008
-0.0005	-0.0006	-0.001	-0.0006	0.0129	-0.0002
-0.0002	-0.0001	-0.0006	-0.0008	-0.0002	0.015

The developed LMNN has five input nodes (membership values of P_D in five fuzzy categories of very low, medium etc) and 7 output nodes (6 nodes for unit outputs, one for incremental fuel cost). The optimum size of the neural network has been obtained by training LMNN models having different no. of hidden nodes for the training error goal of 1×10^{-3} pu. The training performance of the neural networks having different structures has been shown in Table 4. As can be observed from Table 4, the LMNN model having 18 hidden nodes (5-18-7) is the most efficient structure, as it required the least training time for the same error goal.

Table 4.Training Performance of Hybrid LMNN (HNFS) with different structures for 6-units system

S.No	No. of Hidden nodes	Training time	No. of Epochs
1	11	1.0 s	6
2	**18**	**.25 s**	**5**
3	20	.7 s	15
4	24	.4 s	7
5	28	2.1 s	33

The testing performance (percentage testing error) of the trained LMNN for all the 60 testing patterns is compared with conventional method and plotted in Fig. 3-Fig. 9. The figures clearly show that the trained neural network produces accurate results i.e. almost negligible error for all the testing patterns for all the seven outputs (generations, incremental fuel cost (lambda)). Result of about 8 testing patters have been compared in Table 5 and Table 6 with conventional results to show that the developed hybrid approach(HNFS) is capable of computing the real power generations and incremental cost.

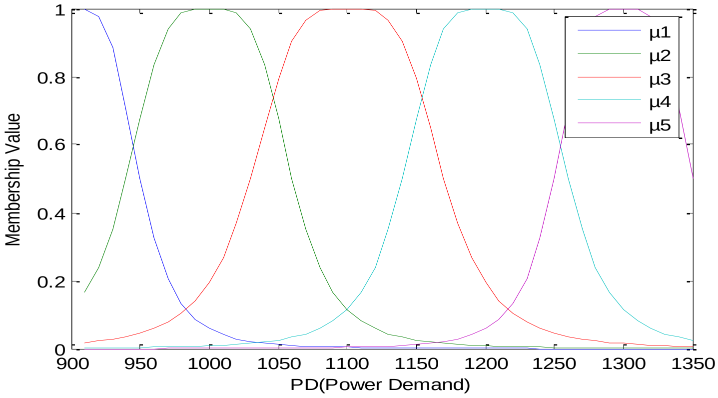

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Fig. 2. Fuzzy modeling of power demand for ED (6-unit system)

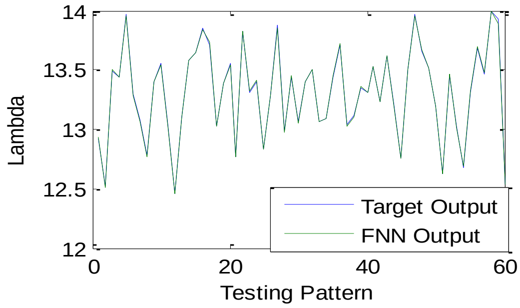

Fig. 3.Results for Lambda of 6-Generating unit System

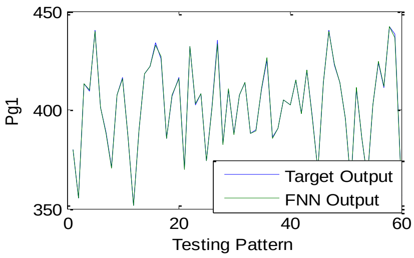

Fig. 4.Results for power allocation of unit-one of 6-Generating unit System

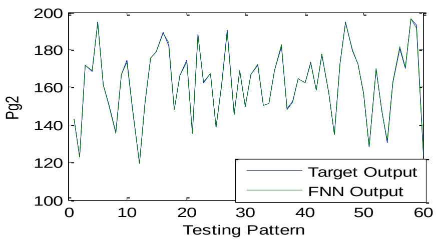

Fig. 5.Results for power allocation of unit-two of 6-Generating unit System

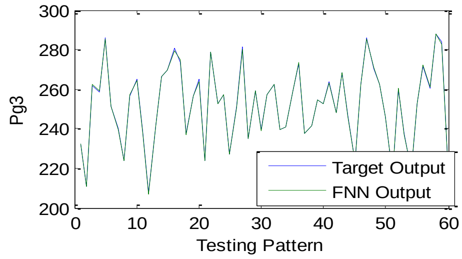

Fig. 6.Results for power allocation of unit-three of 6-Generating unit System

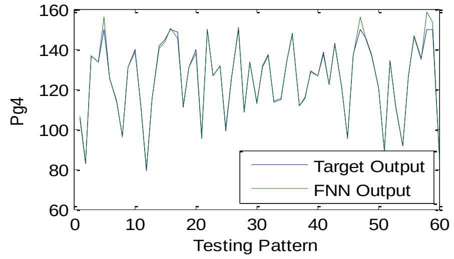

Fig. 7.Results for power allocation of unit-four of 6-Generating unit System

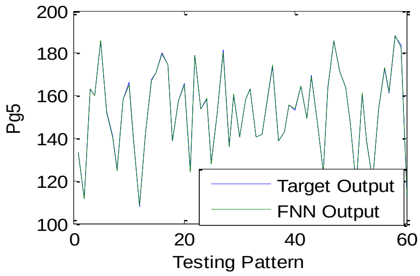

Fig. 8.Results for power allocation of unit-five of 6-Generating unit System

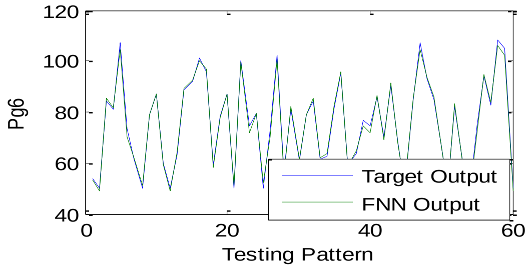

Fig. 9.Results for power allocation of unit-six of 6-Generating unit System

Table 5.Testing Performance of The (5-18-7) hybrid LMNN (HNFS)

S.no.	Output value	PD=902.513		PD=951.576		PD=1014.646		PD=1067.224	
		Classical	HNFS	Classical	HNFS	Classical	HNFS	Classical	HNFS
1.	Lambda	12.445	12.446	12.631	12.633	12.866	12.865	13.033	13.035
2.	Pg1	351.091	351.099	362.218	362.228	376.242	376.250	386.103	386.113
3.	Pg2	119.257	119.265	128.554	128.563	140.264	140.272	148.549	148.558
4.	Pg3	206.879	206.888	216.572	216.582	229.126	229.137	237.825	237.832
5.	Pg4	78.848	78.857	88.959	88.942	102.192	102.198	111.306	111.317
6.	Pg5	107.715	107.722	117.603	117.609	130.098	130.107	138.871	138.879
7.	Pg6	50.000	50.010	50.000	50.005	50.483	50.486	59.465	59.469

Table 6.Testing Performance of The (5-18-7) hybrid LMNN (HNFS)

S.no.	Output value	PD=1100.293		PD=1162.256		PD=1249.381		PD=1332.736	
		Classical	HNFS	Classical	HNFS	Classical	HNFS	Classical	HNFS
1.	Lambda	13.138	13.139	13.336	13.339	13.615	13.617	13.928	13.930
2.	Pg1	392.305	392.314	403.926	403.934	420.264	420.272	438.075	438.082
3.	Pg2	153.771	153.780	163.579	163.585	177.421	177.429	193.084	193.093
4.	Pg3	243.308	243.317	253.604	253.612	268.133	268.141	284.301	284.309
5.	Pg4	117.053	117.062	127.852	127.861	143.106	143.113	150.000	150.008
6.	Pg5	144.389	144.396	154.730	154.739	169.273	169.279	184.054	184.059
7.	Pg6	65.109	65.118	75.676	75.684	90.511	90.518	105.091	105.099

3.2 Thirteen Generating Unit System

The cost coefficient data along with generating limits for the Thirteen-unit power system i and B-coefficients have been taken [10]. In this case also, 300 load patterns were generated, changing the load at different buses randomly between 2000MW and 2400 MW in wide range. The generated loads were fuzzified using eq (6) and the data selected for fuzzification which is given in Table 7. The fuzzified demand for the full range is plotted in Figure 10 showing the memberships in all five categories. Out of 300 patterns, 240 patterns were used for training using Levenberg-Marquardt algorithm based feed forward network, while the remaining 60 patterns were used for the testing purpose.

Table 7.Data for fuzzy modeling of power demand for 13-unit system

Linguistic Category for P_D	Very Small	Small	Medium	Large	Very Large
a_i	2000	2090	2180	2270	2360
b_i	60	60	70	60	65

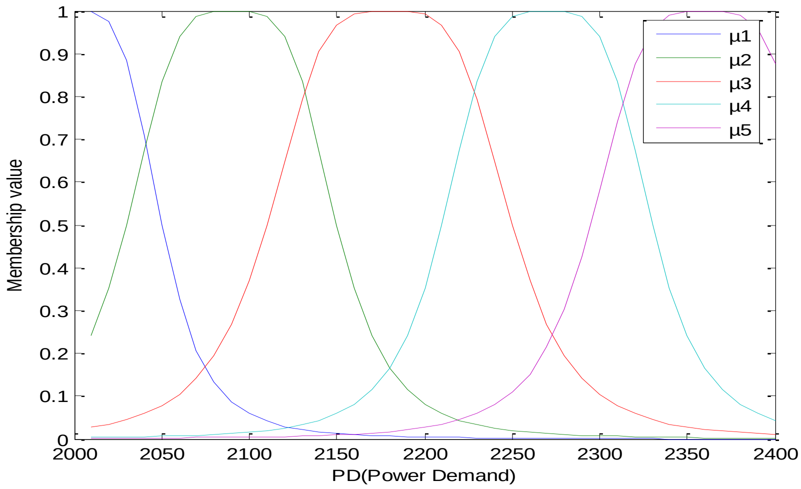

Fig. 10. Fuzzy modeling of power demand for ED (13-unit system)

Table 8.Training Performance of hybrid LMNN for different structures for 13-unit system

S.No.	No. of Hidden nodes	Training time	No. of Epochs
1	**11**	**0.6 s**	**8**
2	19	1.2 s	14
3	22	1.5 s	12
4	25	1.7 s	12
5	30	3.6 s	20

After training different structures for different number of hidden nodes for the training error goal of 1×10^{-3} pu, the optimum size of LMNN for 13-unit economic dispatch problem was found to be (5-11-14). The training performance of the neural networks having different structures has been shown in Table 8. The results of the trained neural network for the previously unseen 60 patterns have been shown in Fig 11-Fig 24. The testing results of 4 patterns are shown in Table 9 and are compared with those obtained from classical lambda iteration method. It can be seen that the proposed LMNN based hybrid method (Hybrid Neuro Fuzzy System) is accurate and trains very fast without facing local minima problems.

Table 9.Testing Performance off The (5-11-14) hybrid LMNN (HNFS)

S.no.	Out Put Value	PD=2004.772		PD=2240.795		PD=2349.380		PD=2384.915	
		Classical	HNFS	Classical	HNFS	Classical	HNFS	Classical	HNFS
1	Lambda	9.153	9.155	9.498	9.496	9.488	9.489	9.546	9.547
2	Pg1	60	60	60	60	60	60	60	60
3	Pg2	60	60.003	60	60.006	94.566	94.569	101.806	101.8
4	Pg3	60	60.002	106.16	106.17	101.02	101.03	108.795	108.8
5	Pg4	60	60.002	99.564	99.569	93.637	93.638	100.802	100.8
6	Pg5	60	60.004	60	60.002	90.769	90.762	97.696	97.7
7	Pg6	60	60.002	102.07	102.07	96	96.006	103.366	103.4
8	Pg7	82.713	82.715	120	120.01	120	120.01	120	120
9	Pg8	80.246	80.242	120	120	120	120	120	120
10	Pg9	83.927	83.93	120	120	120	120	120	120
11	Pg10	55	55.003	55	55.004	120	120.01	120	120
12	Pg11	680	680	680	680	680	680	680	680
13	Pg12	360	360	360	360	360	360	360	360
14	Pg13	360	360	360	360	360	360	360	360

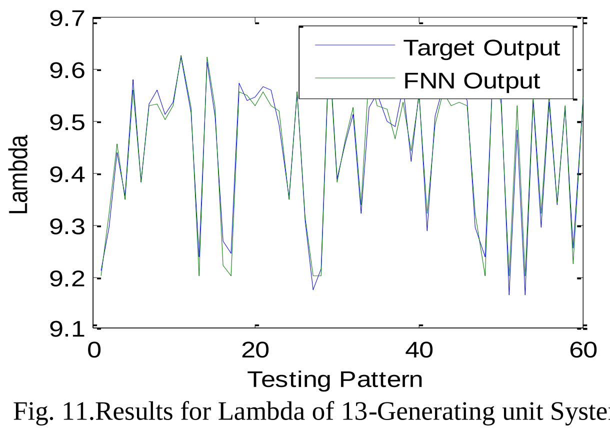

Fig. 11.Results for Lambda of 13-Generating unit System

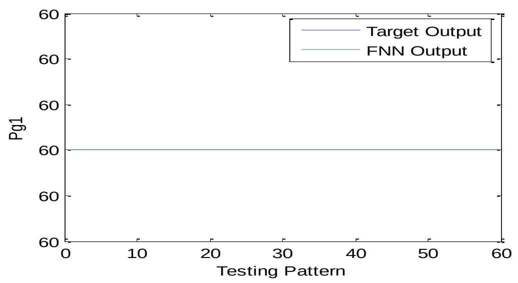

Fig. 12.Results for cost of operation for unit one of 13-Generating unit System

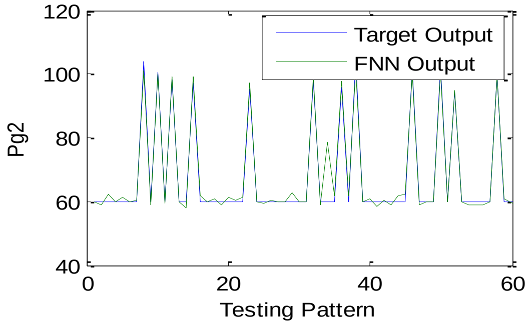

Fig. 13.Results for cost of operation for unit two of 13-Generating unit System

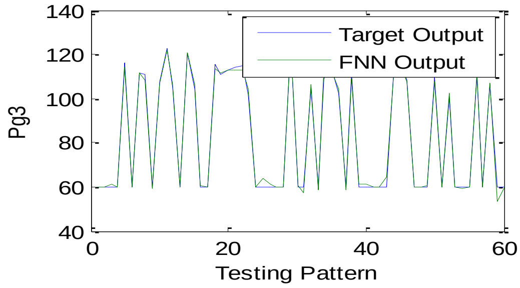

Fig. 14.Results for cost of operation for unit three of 13-Generating unit System

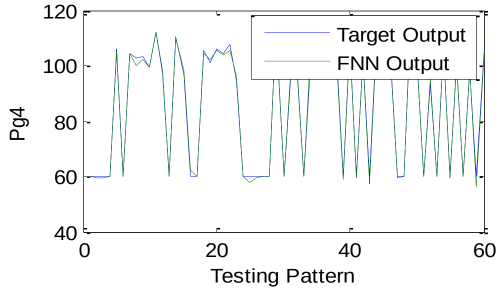

Fig. 15.Results for power generation for unit four of 13-Generating unit System

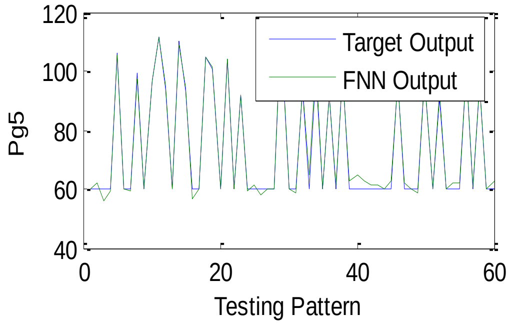

Fig. 16.Results for cost of operation for unit five of 13-generating unit system

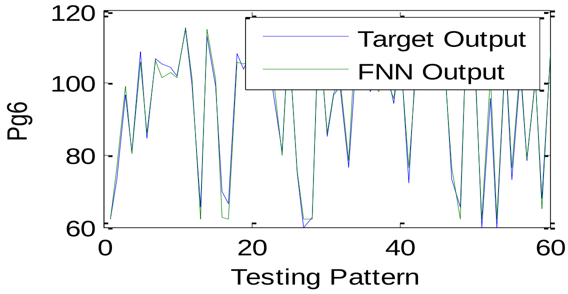

Fig. 17. Results for cost of operation for unit six of 13-generating unit system

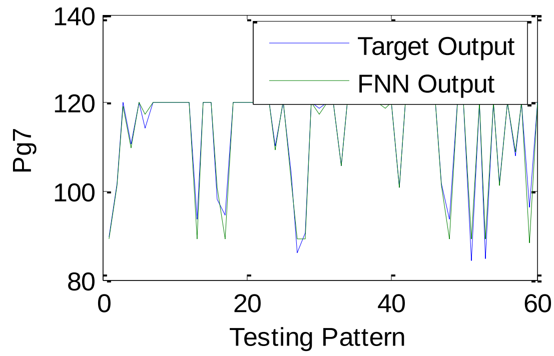

Fig.18. Results for cost of operation for unit seven of 13-generating unit system

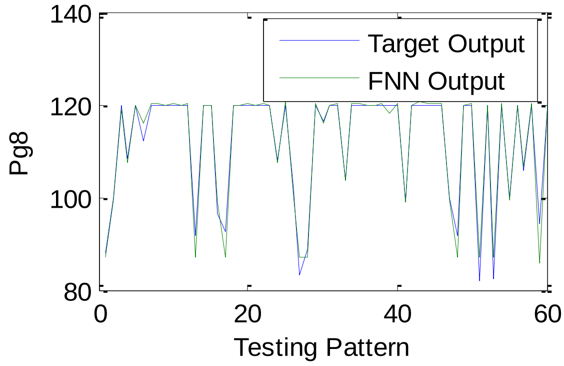

Fig.19. Results for cost of operation for unit eight of 13-generating unit system.

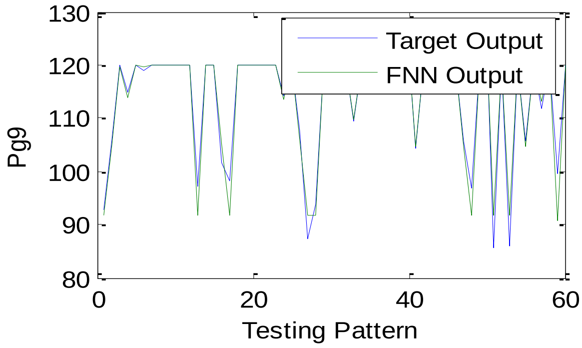

Fig.20. Results for cost of operation for unit nine of 13-generating unit system.

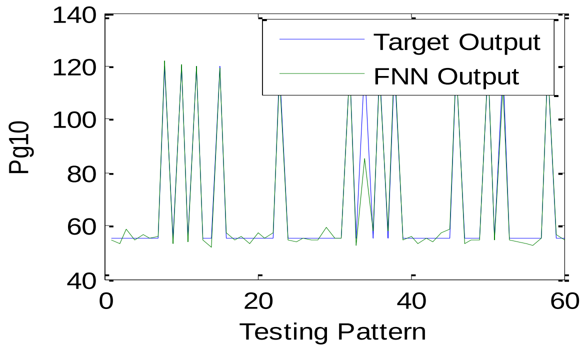

Fig.21. Results for cost of operation for unit ten of 13-generating unit system

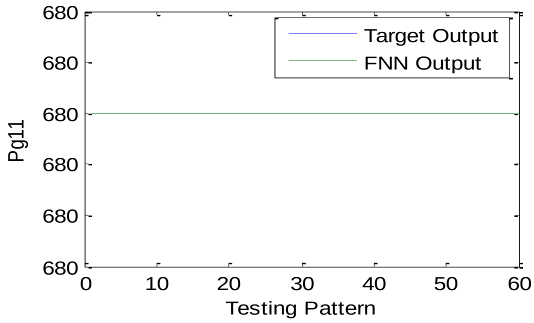

Fig.22. Results for cost of operation for unit eleven of 13-generating unit system.

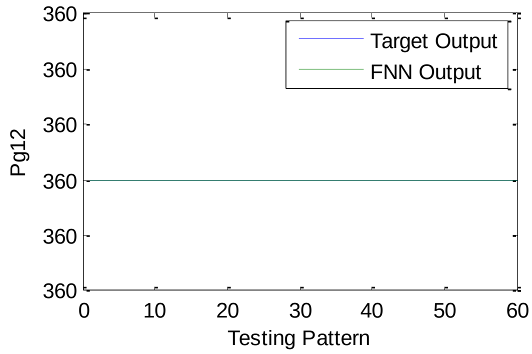

Fig.23. Results for cost of operation for unit twelve of 13-generating unit system.

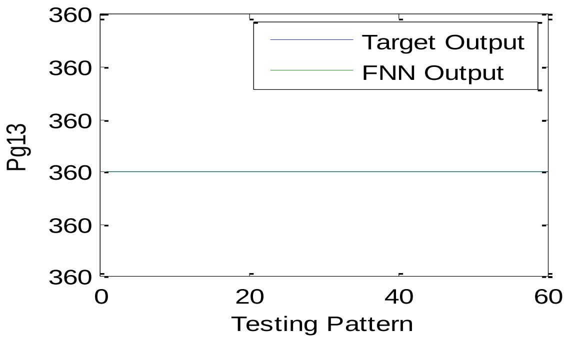

Fig.24. Results for cost of operation for unit thirteen of 13-generating unit system.

IV. Conclusion

The paper proposes an efficient hybrid method for handling the complex problem of optimum generation allocation for constantly changing loads, keeping operating cost at their least level. Classical lambda iteration method for economic load dispatch problem for a practical power system is found to be too time consuming for effective real-time implementation.

The proposed hybrid Levenberg-Marquardt based neural network (HNFS) is trained to provide the optimal value of incremental cost and economic generation dispatch on all the committed generating units for a given power demand. Due to the fuzzification of input power demand the network is expected to perform well under practical conditions where the data may be vague, noisy or incorrect. During testing phase, the trained hybrid network provided accurate results for previously unseen patterns. The proposed method is noise tolerant and can adapt to changing system conditions very easily. As the training of the LMNN using Levenberg-Marquardt algorithm is extremely fast, it may be used for on-line implementation at energy management centre.

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